



Statistical mechanics of the focusing nonlinear Schrödinger equation

Consider a Hamiltonian equation on \mathbb{R}^d :

Let $H: \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$ be a Hamiltonian, and p, q solve

$$\begin{cases} \partial_t p = \mathcal{J} \frac{\partial H}{\partial q}, \\ \partial_t q = -\mathcal{J} \frac{\partial H}{\partial p}, \end{cases}$$

where $\mathcal{J}: \mathbb{R}^{2d} \rightarrow \mathbb{R}^{2d}$ is skew-adj. $\mathcal{J}^* = -\mathcal{J}$ and $\mathcal{J}^2 = -\text{Id}$,

We say that a measure μ is conserved by the flow

if $\forall F: \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$ cont. and bdd.,

$$\int F(p(t), q(t)) d\mu(p_0, q_0) = \int F(p_0, q_0) d\mu(p_0, q_0).$$

The following measures are conserved by Hamiltonian flows:

1. Lebesgue: $dp dq \in$ Liouville's thm.

2. Gibbs measure: $\frac{1}{Z} \exp(-H(p, q)) dp dq$ \in probability

3. For every $M: \mathbb{R}^d \times \mathbb{R}^d \rightarrow \mathbb{R}$ that is constant along the flow, probability $\rightarrow \frac{1}{Z_M} \exp(-H(p, q)) \exp(-M(p, q)) dp dq$.

We call these (generalised) grand canonical measure

In Statistical mechanics, 2. and 3. ^{non-standard} describe the eq. of the system.

Qk: If M is conserved, then $\forall \beta: \mathbb{R} \rightarrow \mathbb{R}$,

$\beta(M)$ is also conserved.

Important: We want our invariant measures to be probabilities, whenever possible.

Pathological example: $\dot{x} = 1$, or $x(t) = x + t$.

Then dx is invariant, but $x(t) \rightarrow \infty \quad \forall x_0$.

Therefore, dx has nothing to do with the equilibrium.

Consider NLS, $v: \mathbb{T}^d \rightarrow \mathbb{C}$.

$$\begin{cases} i\partial_t v = -\Delta v \pm \sigma |v|^{p-2} v \\ v(0) = 0. \end{cases}$$

This is Hamiltonian, with $p = \operatorname{Re} v$, $q = \operatorname{Im} v$,

$$H(p, q) = H(v) = \mp \frac{\sigma}{p} \int_{\mathbb{T}^d} |v|^p + \frac{1}{2} \int_{\mathbb{T}^d} |\nabla v|^2.$$

Moreover, $M(v) = \int_{\mathbb{T}^d} |v|^2$ is also conserved.

Grand-canonical measure: formally

$$d\mu(u) = \frac{1}{Z} \exp(-H(u) - \frac{1}{2} M(u)) du d\bar{u}.$$

Defocusing case: sign +:

$$d\mu(u) = \frac{1}{Z} \exp\left(-\frac{\sigma}{p} \int_{\mathbb{T}^d} |u|^p - \frac{1}{2} \int_{\mathbb{T}^d} |\nabla u|^2 - \frac{1}{2} \int_{\mathbb{T}^d} |u|^2\right) du d\bar{u}$$

densities
Gaussian

"Standard" \mathbb{Q}_d^p measure on \mathbb{T}^d . Defined:

- $d=1$: $\forall p > 0$.
- $d=2$: $p=2k, k \in \mathbb{N}$. Requires renormalization.
- $d=3$: Only $p=2$ (Gaussian), $p=4$. For $p=4$, \mathbb{Q}_3^4 and Gaussian are mutually singular.

Focusing case: sign -

We want to build the grand-canonical ensemble:

$$d\mu(u) = \frac{1}{Z} \exp\left(\frac{\sigma}{p} \int_{\mathbb{T}^d} |u|^p - \frac{1}{2} \int_{\mathbb{T}^d} |\nabla u|^2 - \frac{1}{2} \int_{\mathbb{T}^d} |u|^2\right) \mathbb{1}_{\{M(u) \leq \beta\}} du$$

Lebowitz - Rose - Speer '88: odd mass cutoff.

Heuristic: Gagliardo - Nirenberg - Sobolev: for $2 \leq p \leq p^* = \begin{cases} \frac{2d}{d-2} & \text{if } d \geq 3 \\ \infty & \text{if } d \leq 2 \end{cases}$

$$\|u\|_{L^p(\mathbb{R}^d)}^p \leq C_{GNS}(p) \|u\|_{L^2}^{\frac{p+d-pd}{2}} \|\nabla u\|_{L^2}^{\frac{pd}{2}-d} \quad p \neq \infty,$$

Therefore, for $\|u\|_2 \leq \kappa^{1/2}$, we expect:

• ρ exists for every κ when $\frac{pd}{2} - d < 2 \Leftrightarrow p < \frac{4+2d}{d}$, i.e.

• When $p = \frac{4+2d}{d}$,

ρ exists (\Rightarrow a probability measure)

whenever

$$C_{\text{GNS}}(p) \kappa^{\frac{p+d}{2} - \frac{pd}{4}} \frac{\sigma}{p} < \frac{1}{2},$$

and maybe also =.

$$p < 6 \quad \text{in } d=1$$

$$p < 4 \quad \text{in } d=2$$

$$p < \frac{10}{3} \quad \text{in } d=3$$

$$p < 3 \quad \text{in } d=4$$

Theorem:

($d=1$) (LRS '88) When $d=1$, the measure ρ exists under the above conditions.

(Oh-Sosoe - T. '21): When $p=6$, in the = case, the measure exists as well

($d=2$) Even under appropriate

renormalisation, the measure does not exist when $p=4$, for any value of σ, κ .

(Brydges - Slade '06, Oh - Seong - T. '23)

It does exist when $p=3$, for any value of σ, κ .

($d=3$) When $p=3$, the measure exists when $\sigma \ll 1$, and does not exist when $\sigma \gg 1$. The value of κ is irrelevant

1. Gaussian measure $\mu \sim \frac{1}{Z} \exp\left(-\frac{1}{2} \int |\nabla u|^2 - \frac{1}{2} \int |u|^2\right)$.

We have that

$\mu = \text{Law}(X)$, where

$$X = \frac{1}{(2\pi)^{d/2}} \sum_{n \in \mathbb{Z}^d} \frac{g_n}{\sqrt{1+n^2}} e^{i n \cdot x} =: \sum_{n \in \mathbb{Z}^d} \frac{g_n}{\langle n \rangle} e_n(x),$$

and $g_n \sim N_{\mathbb{C}}(0, 1)$, i.i.d.. We have that (Ex.)

$$\bullet \mathbb{E} \|X\|_{H^s}^2 = \mathbb{E} \sum_{n \in \mathbb{Z}^d} \frac{\langle n \rangle^{2s} |g_n|^2}{\langle n \rangle^2} = \sum_{n \in \mathbb{Z}^d} \frac{1}{\langle n \rangle^{2-2s}} < \infty$$

iff $s < 1 - \frac{d}{2}$. This is sharp, i.e.

$$\|X\|_{H^{1-d/2}}^2 = \infty \text{ a.s. (Ex.)}$$

• Similarly,

$$\begin{aligned} \mathbb{E} |(1-\Delta)^{s/2} X(x)|^2 &= \mathbb{E} \left| \frac{1}{(2\pi)^d} \sum_{n \in \mathbb{Z}^d} \frac{\langle n \rangle^s g_n}{\langle n \rangle^2} e^{i n \cdot x} \right|^2 \\ &\stackrel{\text{Ind.}}{=} \sum_{n \in \mathbb{Z}^d} \frac{1}{(2\pi)^d} \frac{1}{\langle n \rangle^{2-2s}} = \frac{1}{(2\pi)^d} \mathbb{E} \|X\|_{H^s}^2. \end{aligned}$$

• For $d=1$,

$$\mathbb{E} \|X\|_{L^p}^p \stackrel{\text{Fubini}}{=} \int \mathbb{E} |X(x)|^p dx$$

$$= \int c_p \left(\mathbb{E} |X(x)|^2 \right)^{p/2} dx$$

$$= \int \frac{c_p}{2\pi} \left(\mathbb{E} \|X\|_{L^2}^2 \right)^{p/2} dx$$

$$= c_p \left(\mathbb{E} \|X\|_{L^2}^2 \right)^{p/2}$$

$$< \infty.$$

This is enough to define

$$d\mu^+(v) := \frac{\exp\left(-\frac{\sigma}{P} \int |v|^P\right) d\mu}{\int \exp\left(-\frac{\sigma}{P} \int |v|^P\right) d\mu}.$$

Variational formula (easy version)

let $F: H^{1-d/2-\varepsilon} \rightarrow \mathbb{R}$ be a meas. functional, bounded below. Then

$$\log \int \exp(F(v)) d\mu(v)$$

$$\leq \mathbb{E} \left[\sup_{v \in H^1} F(x+V) - \frac{1}{2} \|V\|_{H^1}^2 \right].$$

1-d focusing case:

We build

$$\exp\left(\frac{\sigma}{P} \int_{\mathbb{T}^d} |v|^P \mathbb{1}_{\{m(v) \leq K\}}\right) d\mu$$

• GNS on the torus: $\forall \varepsilon > 0$

$$\|V\|_{L^P(\mathbb{T})}^P \leq C_{\text{GNS}}(P) (1+\varepsilon) \|V\|_{L^2}^{P/2+1} \|V\|_{H^1}^{P/2-1} + C_\varepsilon \|V\|_{L^2}^P.$$

• let $v_\varepsilon = e^{\varepsilon^2 \Delta} v$. Then $\forall 1 < p < \infty$, $\forall A \geq 0$

$$\|X - X_\varepsilon\|_{L^p} \approx \varepsilon^s \|(-\Delta)^{s/2} X\|_{L^p},$$

$$\|X_\varepsilon\|_{H^1} \approx \varepsilon^{-(1-s)} \|X\|_{H^s}.$$

We just need to estimate

$$\mathbb{E} \left[\sup_{V \in H^1} \frac{\sigma}{p} \int |X + V|^p \mathbb{1}_{\{M(X+V) \leq \kappa\}} - \frac{1}{2} \|V\|_{H^1}^2 \right]$$

$$\stackrel{\uparrow}{=} \mathbb{E} \left[\sup_{W \in H^1} \frac{\sigma}{p} \int |X - X_\varepsilon + W|^p \mathbb{1}_{\{M(X - X_\varepsilon + W) \leq \kappa\}} - \frac{1}{2} \|W - X_\varepsilon\|_{H^1}^2 \right]$$

$V = -X_\varepsilon + W$

Young

$$\leq \mathbb{E} \left[\sup_{W \in H^1} \frac{\sigma(1+\eta)}{p} \int |W|^p \mathbb{1}_{\left\{ \|W\|_{L^2} \leq \kappa^{1/2} + M(X - X_\varepsilon) \right\}} - \frac{1-\eta}{2} \|W\|_{H^1}^2 \right]$$

$$+ \mathbb{E} \left[C(\eta, \sigma, p) \left(\int |X - X_\varepsilon|^p + \|X_\varepsilon\|_{H^1}^2 \right) \right].$$

Pick $\varepsilon^{1/4} = \frac{\eta}{(1 + \|X\|_{H^{1/4}})},$ or $\varepsilon = \frac{\eta^4}{(1 + \|X\|_{H^{1/4}})^4}.$

Then $\eta (X - X_\varepsilon) \leq \eta$,

$$\|X - X_\varepsilon\|_{L^p}^p \leq \|X\|_{L^p}^p,$$

$$\|X_\varepsilon\|_{H^1}^2 \leq \frac{(1 + \|X\|_{H^1/4})^8}{\eta^6}.$$

We obtain

1.

$$\leq \sup_{W \in H^1} C_{GNS} (K^{1/2} + C\eta)^{p/2+1} \frac{(1+\eta)^2}{\eta^p} \|W\|_{H^1}^{p/2-1} - \frac{1-\eta}{2} \|W\|_{H^1}^2$$

$< +\infty$ if

• $p/2 - 1 < 2 \Leftrightarrow p < 6$, or

• $p = 6$ and $C_{GNS}(6) (K^{1/2} + C\eta)^4 (1+\eta)^2 \frac{\sigma}{p} \leq \frac{1-\eta}{2}$.

Since η is arbitrary, we get

$$\boxed{C_{GNS}(6) K^2 \frac{\sigma}{p} < \frac{1}{2}}$$

2. Finite $\forall \eta, \sigma, p$.

2d: Expected numerology: $p \leq 4$.

Can we normalise the measure

$$\exp\left(\frac{\sigma}{4} \int |u|^4\right) \mathbb{1}_{\{M(u) \leq k\}} d\mu(u)$$

for some σ, k ?

Remark: This is already a σ -finite measure

We try to repeat the same proof.

$$\frac{\sigma}{4} \int |X+V|^4 \lesssim \sigma \|V\|_{H^1}^2 \|V\|_{L^2}^2 + \text{error}.$$

$$K \geq M(X+V) := \underbrace{M(X)}_{\text{finite}} + \underbrace{2 \int X V}_{L^2} + \underbrace{\|V\|_{L^2}^2}_{\text{good}}$$

bad: $\neq \|V\|_{L^2}$.

Issue: if $V = -\lambda X + W$, $W \perp_{L^2} X$, then

$$M(X+V) = M(X) - 2\lambda \|X\|_{L^2}^2 + \lambda^2 \|X\|_{L^2}^2 + \|W\|_{L^2}^2$$

$$\text{For } \lambda \ll 1, \approx M(X) - \lambda(2-\lambda)\infty + \|W\|_{L^2}^2$$

\uparrow can be very big.

Q: How do we make this rigorous?

Thm: (Borel - Dupuis formula)

Let F be measurable and bounded. Let $X(t)$

be the cylindrical Brownian motion

$$X(t) = \operatorname{Re} \sum_{n \in \mathbb{Z}^d} \frac{1}{\langle n \rangle} W_n(t),$$

where $\{W_n(t)\}$ are i.i.d. - Brownian motions on \mathbb{C} ,
with $\mathbb{E} |W_n(t)|^2 = t$.

Let

$$H'_0 = \{V \in L^2(\Omega, H^1) : \dot{V} \in L^2(\Omega, H^1), V \text{ prog. measurable}\}$$

Then

$$\mathbb{E} [\exp(F(X))] = \sup_{V \in H'_0} \mathbb{E} \left[F(X(\underline{1}) + V(\underline{1})) - \frac{1}{2} \int_0^1 \|\dot{V}(t)\|_{H^1}^2 dt \right]$$

Rk: Removing the condition V prog. measurable, the

sup is realised when $\dot{V} \equiv \text{const} \equiv V(\underline{1})$. This implies

the simplified version

Rk: We are going to apply this on F not bounded.

See exercises.

Thus $\forall \sigma > 0, \kappa > 0$, we have that

$$\mathbb{E} \left[\exp \left(\frac{\sigma}{4} \int_0^1 u^4 \right) \mathbb{1}_{\{ |M(u)| \leq \kappa \}} \right] = \infty$$

$\forall \kappa > 0$.

By B.D., $\forall M \geq 1$, we need to find V adapted

s.t.

$$\mathbb{E} \left[\frac{\sigma}{4} \int_0^1 (X+V)^4 \mathbb{1}_{\left\{ \left| \int_0^1 X^2 + 2 \int_0^1 X V + \int_0^1 V^2 \right| \leq \kappa \right\}} - \frac{1}{2} \int_0^1 \| \dot{V} \|_{H^1}^2(s) \right] \geq \eta.$$

Ansatz: Recall the estimate

$$\|V\|_{L^4}^4 \leq \|V\|_{L^2}^2 \|V\|_{H^1}^2.$$

We want V s.t.

- The \leq is "almost sharp"
- $\int V(1)^2 \gg 1$
- $\left| \int X^2 \right| + 2 \int X V + \int |V(1)|^2 < 1$.
- \dot{V} adapted.

$$\dot{V}(s) = \alpha_\varepsilon f - \dot{\tilde{X}}_\varepsilon(s),$$

where $\tilde{X}_\varepsilon(\mathbb{1})$ is a (Gaussian) smooth approximation of X . Then

$$\mathbb{E} M(X+V):$$

$$= \int : X(\mathbb{1})^2 : - 2 \int X(\mathbb{1}) \tilde{X}_\varepsilon(\mathbb{1}) + \int (\tilde{X}_\varepsilon(\mathbb{1}))^2 \\ + 2 \int (X(\mathbb{1}) - \tilde{X}_\varepsilon(\mathbb{1})) \cdot \alpha_\varepsilon f \\ + \alpha_\varepsilon^2 f^2.$$

$$= \int : (X(\mathbb{1}) - \tilde{X}_\varepsilon(\mathbb{1}))^2 :$$

$$- 2 \mathbb{E} \left[\int X(\mathbb{1}) \tilde{X}_\varepsilon(\mathbb{1}) \right] + \mathbb{E} \left[\int X_\varepsilon(\mathbb{1})^2 \right] \\ + 2 \int (X(\mathbb{1}) - \tilde{X}_\varepsilon(\mathbb{1})) \cdot \alpha_\varepsilon f \\ + \alpha_\varepsilon^2 f^2.$$

$$(I): \lesssim \varepsilon^\theta \text{ for some } \theta > 0.$$

$$(II) \sim - \mathbb{E} \left[\int (\tilde{X}_\varepsilon(\mathbb{1}))^2 \right] \sim \log \varepsilon$$

$$(III) \lesssim \varepsilon^\theta \text{ for } f \text{ very localised}$$

$$(IV) = \alpha_\varepsilon^2.$$

Pick $\alpha_\varepsilon^2 = 2 \mathbb{E} \left[\int X(t) \tilde{X}_\varepsilon(t) \right] - \mathbb{E} \left[\tilde{X}_\varepsilon(t)^2 \right]$

Then $\mathbb{E} |M(X+V)|^2 \lesssim \varepsilon^0$,

$$\int |X+V|^4 \sim \alpha_\varepsilon^4 \int |f|^4 \sim (\log \varepsilon)^2 \|f\|_{H^1}^2,$$

$$\begin{aligned} \int \|V\|_{H^1}^2 &\lesssim \|\tilde{X}_\varepsilon\|_{H_x^1 H_x^1}^2 + \alpha_\varepsilon^2 \|f\|_{H^1}^2 \\ &\lesssim g(\varepsilon) + |\log \varepsilon| \|f\|_{H^1}^2. \end{aligned}$$

Therefore,

$$\mathbb{E} (*) \geq \left(c_1 (\log \varepsilon)^2 - c_2 |\log \varepsilon| \right) \|f\|_{H^1}^2 - g(\varepsilon)$$

Pick $\varepsilon < \varepsilon_0$, $\|f\|_{H^1}^2 > \varepsilon$, and obtain the blowup.

Exercises: One (non-optimal) way to build $\tilde{X}_\varepsilon(s)$.

PK's We automatically get a stronger non-existence result.

let p_ε be some approx. identity as $\varepsilon \rightarrow 0$, and

consider

$$g_\varepsilon = \frac{1}{z_\varepsilon} \exp\left(\frac{\sigma}{4} \int : (p_\varepsilon * u)^4 :\right) \mathbb{1}_{\{M(u) \leq K\}} N.$$

Then ρ_ε has no weak limit in $W^{-1/2, 4+\varepsilon}$.

Pf.: Define the measure

$$\nu_\varepsilon = \frac{1}{Z_\varepsilon^\nu} \exp\left(\frac{\sigma}{4} \int (\rho_\varepsilon * u)^4\right) = \|u\|_{W^{-1/2, 4+\varepsilon}}^M.$$

We can show $\nu_\varepsilon \rightarrow \nu_0$ weakly, $Z_\varepsilon^\nu \rightarrow Z_0^\nu$.

Suppose by contr. $\rho_\varepsilon \rightarrow \rho_0$ on $W^{-1/2, 4+}$.

Then

$$\begin{aligned} \nu_0 &= \lim_{\varepsilon \rightarrow 0} \nu_\varepsilon \\ &= \lim_{\varepsilon \rightarrow 0} \frac{Z_\varepsilon}{Z_\varepsilon^\nu} \exp\left(-\|u\|_{W^{-1/2, 4+\varepsilon}}^M\right) \rho_\varepsilon \\ &= \lim_{\varepsilon \rightarrow 0} \frac{\exp\left(-\|u\|_{W^{-1/2, 4+\varepsilon}}^M\right) \rho_\varepsilon}{\int \exp\left(-\|u\|_{W^{-1/2, 4+\varepsilon}}^M\right) d\rho_\varepsilon(u)} \\ &= \frac{\exp\left(-\|u\|_{W^{-1/2, 4+}}^M\right) \rho_0}{\int \exp\left(-\|u\|_{W^{-1/2, 4+}}^M\right) d\rho_0}. \end{aligned}$$

Therefore,

$$\rho_0 = \Delta \exp\left(\|u\|_{W^{-1/2, 4+}}^M\right) \nu_0$$

$$\int \Rightarrow 1 = \Delta \underbrace{\int \exp\left(\|u\|_{W^{-1/2, 4+}}^M\right) d\nu_0}_{= \infty}$$

= ∞ with the previous proof.

3d case, \mathbb{F}_3^3 .

Issue: We do not expect $\mathbb{F}_3^3 \ll \nu$. We want

to build \mathbb{F}_3^3 as $\lim_{N \rightarrow \infty} f_N$, where

$$f_N = \exp\left(\frac{\sigma}{3} \int (\mathbb{P}_N v)^3\right) \mathbb{1}_{\{|M(v)| \leq k} d\nu(v),$$

for some $\mathbb{P}_N \rightarrow \text{Id}$. cube.

We choose $\widehat{\mathbb{P}_N v}(m) = \hat{v}(m) \mathbb{1}_{\{|v|_\infty \leq N\}}$

This way, $\|\mathbb{P}_N\|_{L^p \rightarrow L^p} \leq p \mathbb{1}$ for $1 < p < \infty$.

Regressively, we build

$$\mathbb{P}_N = \frac{1}{2} \exp\left(\frac{\sigma}{3} \int (\mathbb{P}_N v)^3 - \|v\|_{W^{-\frac{3}{4}, 3}}^{20}\right) d\nu(v) \rightarrow \mathbb{P}_1$$

and then define $f(v) = \exp\left(\|v\|_{W^{-\frac{3}{4}, 3}}^{20}\right) \mathbb{1}_{\{|M(v)| \leq k\}}^{20}$.

We will use the variance formula to build
the measure

Prop.: Suppose that F satisfies the hp. of Exercise

5. Let

$$g_F = \frac{\exp(F(v)) \nu}{\int \exp(F(v)) d\nu(v)}.$$

Then $\forall f$ meas. and bdd.,

$$\int f(v) dg_F(v) = \lim_{n \rightarrow \infty} \mathbb{E}[f(X+V^n)],$$

where V^n is an opt. sequence for

$$\sup_{V \in H_a^1} \mathbb{E} \left[F(X+V) - \frac{1}{2} \int_0^1 \|\dot{V}\|_{H^1}^2(s) \right].$$

Therefore, \exists measure \Leftrightarrow decent properties of (almost) optimisers.

By Bone-Dupuis, for $\mathcal{W} = \mathcal{W}^{-3/4, 3}$,

$$Z_N = \sup_{V \in H^1} \mathbb{E} \left[\int_0^1 P_N(X(1)+V(1))^3 - \|X(1)+V(1)\|_{\mathcal{W}}^2 - \frac{1}{2} \int_0^1 \|\dot{V}(s)\|_{H^3}^2 \right]$$

Recall $X \in C^{1-d/2-\epsilon} = C^{-1/2-\epsilon}$, let $X_N = P_N X$.

$\int X_N(1)^3$ is bad, but $\mathbb{E} \int X_N(1)^3 = 0$.

However, $\int X^2 = C^{-1-\epsilon}$, therefore

$\int X_N^2 \approx V$ is problematic in the limit.

Trick (Boroshkov - Guiselli): Complete the square. Since $X_N^2(s)$ is a martingale,

$$\mathbb{E} \left[\sigma \int_0^1 X_N^2(s) : V(1) - \frac{1}{2} \int_0^1 \langle \dot{V}(s), \dot{V}(s) \rangle_{H^1} ds \right]$$

$$\stackrel{It\ddot{o}}{=} \mathbb{E} \left[\sigma \int_0^1 X_N^2(s) : \dot{V}(s) - \frac{1}{2} \int_0^1 \langle \dot{V}(s), \dot{V}(s) \rangle_{H^1} ds \right]$$

$$= \mathbb{E} \left[\sigma \int_0^1 \langle (-\Delta)^{-1} : X_N^2(s), \dot{V}(s) \rangle_{H^1} - \frac{1}{2} \int_0^1 \langle \dot{V}(s), \dot{V}(s) \rangle_{H^1} ds \right]$$

$$= \mathbb{E} \left[-\frac{1}{2} \int_0^1 \|\dot{V} - \sigma (-\Delta)^{-1} : X_N^2(s)\|_{H^1}^2 ds \right]$$

$$+ \frac{1}{2} \mathbb{E} \left[\int_0^1 \|\sigma (-\Delta)^{-1} : X_N^2(s)\|_{H^1}^2 ds \right] = \sigma_N.$$

Call

$$\cdot \dot{Y}_N(s) = \sigma (-\Delta)^{-1} : X_N^2(s) \in C^{1-\varepsilon}$$

$$\cdot W = V - Y_N.$$

Then

$$\log Z_N = \sigma_N$$

$$= \sup_W \mathbb{E} \left[\sigma \int_0^1 X_N \left(P_N(W + Y_N) \right)^2 + \frac{\sigma}{3} \int_0^1 P_N(W + Y_N)^3 - \|X + V\|_{20}^2 - \frac{1}{2} \int_0^1 \|\dot{W}(s)\|_{H^1}^2 ds \right]$$

$$= \sup_W \left[\mathcal{R}_N(X_N, Y_N, W) - \|X + Y_N + W\|_{\mathcal{H}}^2 + \frac{\sigma_N}{3} \left(\mathcal{P}_N W \right)^3 - \frac{1}{2} \int_0^1 \| \dot{W}(s) \|_{H^1}^2 ds \right]$$

Therefore, V is an almost opt. for Z_N

$$\text{iff } W := V - Y_N$$

\Rightarrow an almost opt. for the above.

We have

- Y_N unif. bdd. ($\in N$) $\in C^{1-\varepsilon}$
- X_N " " " $\in C^{-\frac{1}{2}-\varepsilon}$.

Therefore, one can show:

$$\mathcal{R}_N(X_N, Y_N, W) \leq C_\varepsilon(X_N, Y_N) + \varepsilon \int |W|^3 + \varepsilon \|W\|_{H^1}^2.$$

Therefore, we can control $\log Z_N - \sigma_N$ and

consequently $\|W\|_{H^1}^2 + \|W\|_{L^3}^3$ iff we show

$$\sup_{W \in H^1} \mathbb{E} \left[\frac{\sigma_N}{3} \int W^3 - \|X + Y_N + W\|_{\mathcal{H}}^2 - \frac{1}{2} \int_0^1 \| \dot{W} \|_{H^1}^2 \right]$$

$< \infty$.

OK by interpolation with the choice of $2W$.

What about normalisability, i.e.

$$\int \exp(-\|v\|_{\mathbb{R}^2}^2) dv ?$$

Just need to check

$$\sup_{W \in H^1} \mathbb{E} \left[\frac{\tilde{\sigma}}{3} \int W^3 \right] \neq \{f: M(v) \leq k\} - \frac{1}{2} \|W\|_{H^1}^2.$$

Finite for $\tilde{\sigma}$ in neighborhood of $\sigma \Rightarrow$ normalisability

Infinite " " " " " " \Rightarrow non-normalisability

Looks like the $d=2$ case! Same onset?

$$W = -X_M + \nu f. \quad \text{We get}$$

$$\mathbb{E} \left[\frac{\tilde{\sigma}}{3} \int W^3 \right] \approx \nu^3 \mathbb{E} \left[\frac{\tilde{\sigma}}{3} \int f^3 \right] \quad (\text{I})$$

$$\mathbb{E} \left[|M(X + \gamma_N + W)|^\gamma \right] \approx \left| \nu^2 \|f\|_{L^2}^2 - \mathbb{E} \|X_M\|_{L^2}^2 \right|^\gamma \quad (\text{II})$$

$$\mathbb{E} \int_0^1 \|W\|_{H^1}^2 \approx \mathbb{E} \int_0^1 \|X_M\|_{H^1}^2 + \nu^2 \|f\|_{H^1}^2 \quad (\text{III})$$
$$\approx C M^3 + \nu^2 \|f\|_{H^1}^2.$$

If we choose $\|f\|_{L^2}^2 = 1$, $\nu^2 \sim \mathbb{E} \|X_M\|_{L^2}^2 \sim M$,

we can make (II) = 0 (I).

We obtain

$$\text{step } \geq C_1 M^{3/2} \sigma \|f\|_{L^3}^3 - C_2 M^3 - C_3 M \|f\|_{H^1}^2.$$

We have

$$\|f\|_{L^3}^3 \lesssim \|f\|_{L^2}^{3/2} \|f\|_{H^1}^{3/2} \lesssim \|f\|_{H^1}^{3/2} \text{ sharp.}$$

Optimising the above, we pick

$$M^{3/2} \|f\|_{L^3}^3 \sim M \|f\|_{H^1}^2 \Leftrightarrow \|f\|_{H^1}^2 \sim M, \\ \|f\|_{L^3}^3 \sim M^{3/2}$$

\Rightarrow All the terms have size M^3 . If

$\sigma \gg 1$, we obtain the divergence.

What about $\sigma \ll 1$?

Bails down to showing for $\gamma \gg 1$

$$\int w^3 \lesssim |t|^\gamma M(X + Y_n + W) \leq |t|^\gamma + \|W\|_{H^1}^2.$$

$$\approx 1 + \left\| 2 \int X w + \int w^2 \right\|^\gamma + \|W\|_{H^1}^2. \quad (*)$$

Pf.: Define $\widehat{Q_N U}(n) = \widehat{U}(n) \mathbb{1}_{\left\{ \frac{n}{2} \leq |m| < n \right\}}$

Write

$$W = \sum \lambda_N Q_N X + W_N,$$

with $\lambda_N \in \mathbb{R}$, $W_N \perp Q_N X$ in L^2 .

Then

$$2 \int (X w + w^2)$$

$$= 2 \sum \lambda_N \|Q_N X\|_{L^2}^2 + \sum \lambda_N^2 \|Q_N X\|_{L^2}^2$$

$$+ \sum \|W_N\|_{L^2}^2.$$

2 cores.

1. $\int w^2 \Rightarrow -2 \int x w$. Then

$$|2 \int x w + w^2| \sim |\int w^2|, \text{ and } (*)$$

follows from

$$\|w\|_{L^3}^3 \lesssim \|w\|_{L^2}^{3/2} \|w\|_{H^1}^{3/2} \lesssim \|w\|_{L^2}^6 + \|w\|_{H^1}^2$$

OR

for $\gamma \geq 3$.

2. $\int w^2 \lesssim 2|\int x w|$. Then

$$\sum \lambda_N^2 \|Q_N x\|_{L^2}^2 \leq \sum_N \lambda_N^2 \|Q_N x\|_{L^2}^2 + \|w_N\|_{L^2}^2$$

$$\lesssim \sum \lambda_N \|Q_N x\|_{L^2}^2.$$

Fix $N_0 > 0$. We have that

$$\left| \sum_{N \geq N_0} \lambda_N \|Q_N x\|_{L^2}^2 \right| \lesssim \left(\sum_{N \geq N_0} \|Q_N x\|_{L^2}^2 \right)^{1/2} \left(\sum_N \lambda_N^2 \|Q_N x\|_{L^2}^2 \right)^{1/2}$$

$$\left| \sum_{N \geq N_0} \lambda_N \|Q_N x\|_{L^2}^2 \right| \sim \sum_{N \geq N_0} \lambda_N \|Q_N x\|_{H^1} \|Q_N x\|_{H^1}$$

$$\lesssim \left(\sum_{N > N_0} \|Q_N X\|_{H^{-1}}^2 \right)^{1/2} \left(\sum_{N > N_0} \lambda_N^2 \|Q_N X\|_{H^{-1}}^2 \right)^{1/2}$$

$$\lesssim \|P_{>N_0} X\|_{H^{-1}} \|W\|_{H^1}.$$

Call $Z = \sum \lambda_N \|Q_N X\|_{L^2}^2$. We obtain

$$|Z| \lesssim \left(\sum_{N \leq N_0} \|Q_N X\|_{L^2}^2 \right)^{1/2} |Z|^{1/2} + \|W\|_{H^1} \|P_{>N_0} X\|_{H^{-1}}$$

Solving,

$$|Z| \lesssim \sum_{N \leq N_0} \|Q_N X\|_{L^2}^2 + \|W\|_{H^1} \|P_{>N_0} X\|_{H^{-1}}.$$

Lemma: (Ex.)

$$\sum_{N \leq N_0} \|Q_N X\|_{L^2}^2 \leq C N_0 + B_1(X)$$

$$\sum_{N > N_0} \|Q_N X\|_{H^{-1}}^2 \leq C N_0^{-1} + N_0^{-2} B_2(X).$$

where $\mathbb{E} [|B_1|^p + |B_2|^p] \leq C_p < \infty$.

Pick $N_0 \sim 1 + \|W\|_{H^1}^{2/3}$.

We obtain

$$\|W\|_{L^2}^2 \lesssim |z| \lesssim 1 + \|W\|_{H^1}^3, \text{ or}$$

$$\|W\|_{L^2}^6 \lesssim |z|^3 \lesssim 1 + \|W\|_{H^1}^2.$$

The conclusion follows again by

$$\begin{aligned} \|W\|_{L^3}^3 &\leq \|W\|_{L^2}^6 + \|W\|_{H^1}^2 \\ &\lesssim 1 + |z|^3 + \|W\|_{H^1}^2. \end{aligned}$$

Bourgain's invariant measure argument:

Let X Polish, and let $\{\Phi_t : X \rightarrow X\}_{t \geq 0}$ be a flow map, i.e. $\Phi_{t+s} = \Phi_t \circ \Phi_s$, $\Phi_0 = \text{Id}$.

Suppose that $\Phi_0(\cdot)$ is jointly meas. on $\mathbb{R} \times X$.

Let μ an invariant meas. for Φ . Suppose:

1. (LWP) \exists "size function" $z : X \rightarrow \mathbb{R}$, $z \geq 0$
 \exists "LWP time function" $\tau : \mathbb{R}^+ \rightarrow \mathbb{R}^+$, and $K > 1$, st.

$$z(\Phi_s(u_0)) \leq K z(u_0) \quad \forall 0 \leq s \leq \tau(z(u_0)),$$

and $\tau \gtrsim \langle x \rangle^{-\beta}$ for some $\beta \geq 0$.

2. (LDE for μ)

$$\exists \delta > 0 \text{ st. } \int \exp(z(u_0)^\delta) d\mu(u_0) < \infty.$$

Then we have the estimate

$$z(\Phi_t(v_0)) \leq \log(2+t)^{1/\delta} \quad \text{f.o.a.e.}$$

More precisely, we have the LDE for $M \gg 1$

$$-\log \rho \left(\left\{ z(\Phi_t(v_0)) > M \left(\log(2+t) \right)^{1/\delta} \right\} \right) \geq M^\delta.$$

RK: In the stochastic case,

$$v = \mathcal{N}_1(0, \Xi),$$

with invariant measure ρ for the semigroup,

$$\text{define } \Phi_t(v, \Xi) = (v(t), \Xi(-t)).$$

Then $\rho \otimes \text{Law}(\Xi)$ is invariant.

RK: Singular case: usually

- Measurable map $v_0 \rightarrow \Xi$ enhanced data set
- Unknowns v_1, \dots, v_N .
- Solution $v(t) = F_t(\Xi, v_1, \dots, v_N)$.

Define

$$z(v) = \inf \left\{ \|\Xi\|_0 + \|v_1\|_1 + \dots + \|v_N\|_N + 1 + |t|^\alpha \right. \\ \left. : v = F_t(\Xi, v_1, \dots, v_N) \right\}$$

Typically, this is a good size function.